Hii-HAT: an IDL/ENVI Toolkit for Rapid Hyperspectral Inquiry.

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Introduction: Significant challenges face any user of planetary hyperspectral imagery. For the scientist, the sheer volume of data precludes exhaustive manual analysis. For the mission planner, the complex subtleties of hyperspectral images are difficult to summarize in a readily interpretable product. Both experts would benefit from a rapid, robust means to create draft mineralogical maps, summarize novel detections, and generally draw attention to areas of interest for further investigation. In this work we discuss the Hii-HAT (Hyperspectral Image Interactive Helper and Analysis Tools) toolset developed for the IDL/ENVI environment. It attends to the specific requirements of planetary geologists, such as low signal-to-noise ratios and a lack of reference spectra from the surface.

Hii-HAT incorporates several novel algorithms, including the concept of superpixel decomposition for noise removal and image feature enhancement. It assists in the discovery of endmembers, forms mineral maps through interactive unmixing, and assists in the detection of appropriate neutral regions for a given region of interest (ROI). Here we explore its capabilities with imagery from the Compact Reconnaissance Imaging Spectrometer (CRISM) instrument orbiting Mars [1], specifically the 1000-2500nm wavelengths of images (frt0000)3e12, 8158, 863e, and 3fb9.

Superpixels: Manual analysis often focuses on either an individual spectrum at a single pixel or on the mean spectrum of a large ROI. The former approach preserves spatial resolution but is sensitive to measurement noise. The later reduces noise but requires laborious manual segmentation. Automating segmentation, therefore, is of great interest with the caveat that any errors can easily average-out interesting signals.

Many of Hii-HAT's functions exploit a *superpixel* representation that combines benefits from both approaches. Superpixels represent the image as contiguous regions a few tens or hundreds of pixels in area. By erring on the side of oversegmentation, superpixels reduce noise while preserving small signals evident in only a few contiguous image pixels. This preprocessing step can improve further spectral analysis by simply replacing individual pixel spectra by the mean superpixel spectra, yielding three main advantages. First, measurement noise is reduced proportionally to the square root of the superpixel area. Second, the superpixel's boundary can help discern subtle hyperspectral features in otherwise bland areas. Third, reducing the number of spectra required for processing (in our case by 100 times) speeds successive algorithms and enables new classes of automated analysis. Superpixels exploit the fact that physical surface features are spatially contiguous, and spatial constraints identify populations of pixels drawn from the same feature.

Many segmentation strategies might produce reasonable superpixel segmentations. Hii-HAT utilizes the Felzenszwalb graph segmentation method for its computational efficiency and the ability to accommodate any spectral distance metric [2].

Endmember Extraction: Hii-HAT generates several automatic summary products including superpixel-augmented endmember extraction. By the geographic mixing assumption, observed reflectances are linear combinations of several pure endmember materials. These are of great interest as they represent the physically purest minerals in a scene – the archetypes and novelties that drive exploration. A noise-reduced superpixel representation can improve the performance of classical endmember detection algorithms. Contiguous spatial regions in an image are likely to contain similar mineralogy lending a physical interpretation to the shape of the endmember superpixel.

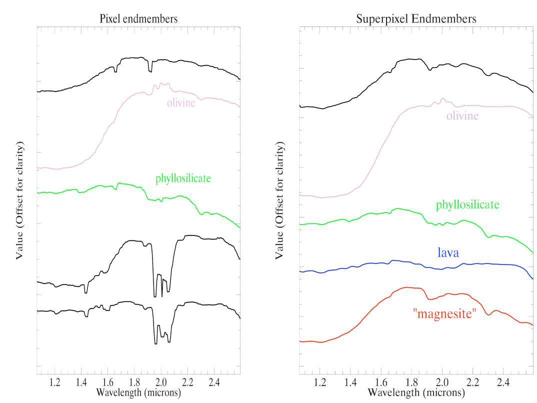

Figure 1. Left: the top five single-pixel endmembers with associated noise corruption. Right: superpixel endmembers with associated mineral identification.

Our approach uses superpixel segmentation followed by Sequential Maximum Angle Convex Cone (SMACC) endmember extraction. Recent tests compared the resulting rank-ordered list of endmembers to expert-provided mineral spectra from salient image features. We compared the mean squared error of the best-matching spectra in both lists to determine correspondence between automatically-detected and expertlabeled constituents. For the same number of endmembers, superpixel representations outperformed pixels, reducing error scores by a factor of 2-5 in each of the four images we considered. Superpixels always captured as many or more distinct mineral classes. Finally, the resulting noise-reduced endmember spectra provide a better match to the expert's minerals. Figure 1 evidences this with the actual endmembers extracted from 3e12 and associated expert identifications where possible.

Interactive Unmixing: Following endmember extraction, unmixing algorithms can compute the proportion that each pure constituent contributes to any image pixel. Hii-HAT includes tools for interactive real-time unmixing with Bayesian Positive Source Separation [3]. This avoids a problem of many least-squares algorithms where optimal solutions often entail a nonzero contribution from all constituents. Bayesian unmixing can encourage "sparse" mixtures by a prior distribution favoring zero-value coefficients (Figure 2).

Superpixel representations also permit more sophisticated and computationally complex analyses. Hii-HAT uses a Gibbs sampling algorithm for probabilistic unmixing that computes distributions over mixing coefficients. This reveals not just the most likely proportions of the endmembers but also the uncertainty associated with each proportion. The technique assists in interpreting features that one can explain by multiple constituents or combinations. The computational requirements of Gibbs sampling would be prohibitive if used on every pixel in a scene.

Neutral Region Detection: Analysts commonly use "neutral" spectra to compensate for atmospheric effects and improve spectral contrast. Dividing a spectrum of interest by a bland, featureless spectrum can enhance features not present in the common background. Unfortunately, discovering neutral regions is a laborious manual process that must often be performed in the time-critical environment of mission planning. Additionally, sensitivity matching requires the same detectors be used for both ROIs and associated neutral regions.

Hii-HAT automatically finds appropriate neutral regions for target ROIs in projected hyperspectral images where image columns no longer correspond to individual detectors. This process entails transforming the target ROI back to the original, unprojected image, detecting a neutral region within the columns shared by the target ROI, and reprojecting the resulting neutral region. The detection step identifies spectrally bland regions by measuring the residual of the best-fitting line to each superpixels' spectrum. The appearance of these spectra is comparable with expert-provided neutral regions (Figures 3 and 4).

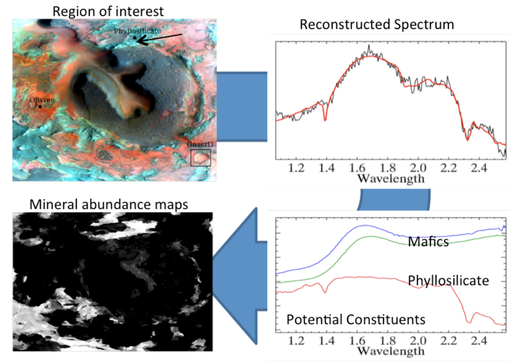

Figure 2. Spectral unmixing in CRISM image 3e12 The reconstruction explains the measurement with a minimal combination of potential consituents.

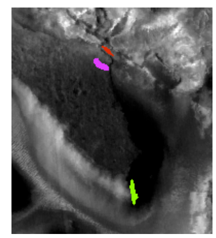

Figure 3. Image 3E12. Red magnesite region is provided as target ROI. Expert-selected neutral region is magenta. The automated selection is green. It subtends the same unprojected columns as the target.

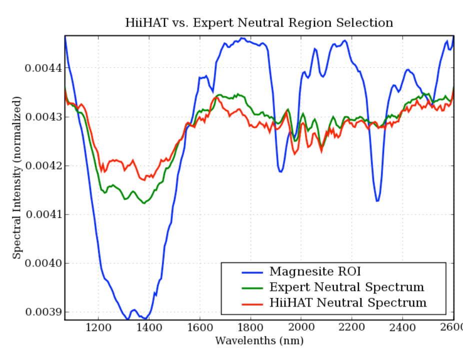

Figure 4. Comparison of neutral spectra produced automatically and by hand.

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References:

[1] S. Murchie et al.,JGR (2007) 112 (5). [2] P. F. Felzenszwalb and D. P. Huttenlocher, (2004) Intl. Journ. of. Computer Vision, 59 (2).[3] Thompson et al., (2009)_IEEE Workshop on Hyperspectral Image and Signal Processing (WHISPERS'09)